

Cooooll: A Deep Learning System for Twitter Sentiment Classification

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1. Introduction

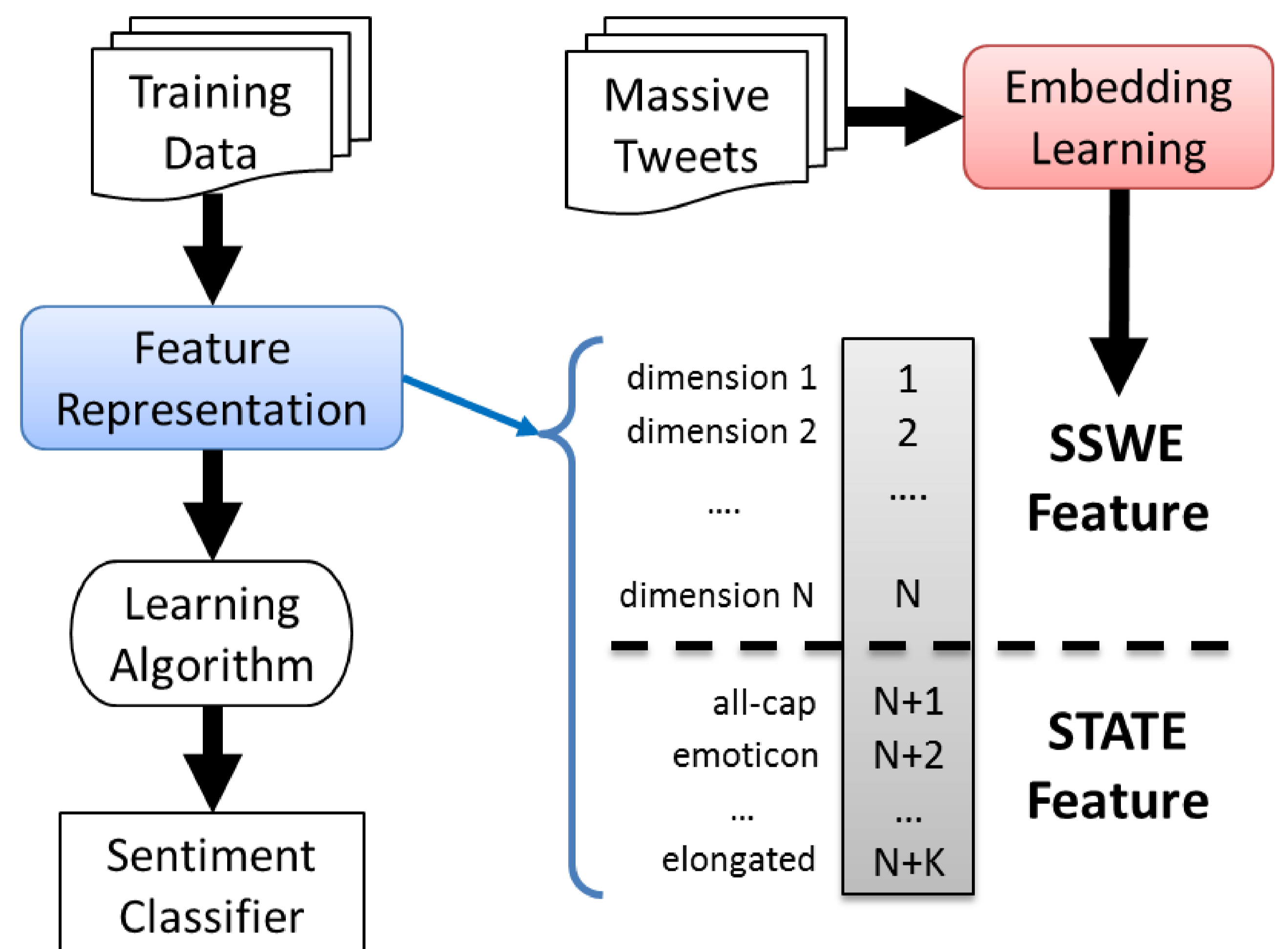
- Twitter sentiment classification aims to classify the sentiment of a tweet as positive/negative/neutral.
- Feature representation is crucial for Twitter sentiment classification
- In this work, we learn features automatically through sentiment-specific word embedding (SSWE).

3. The Official Rank

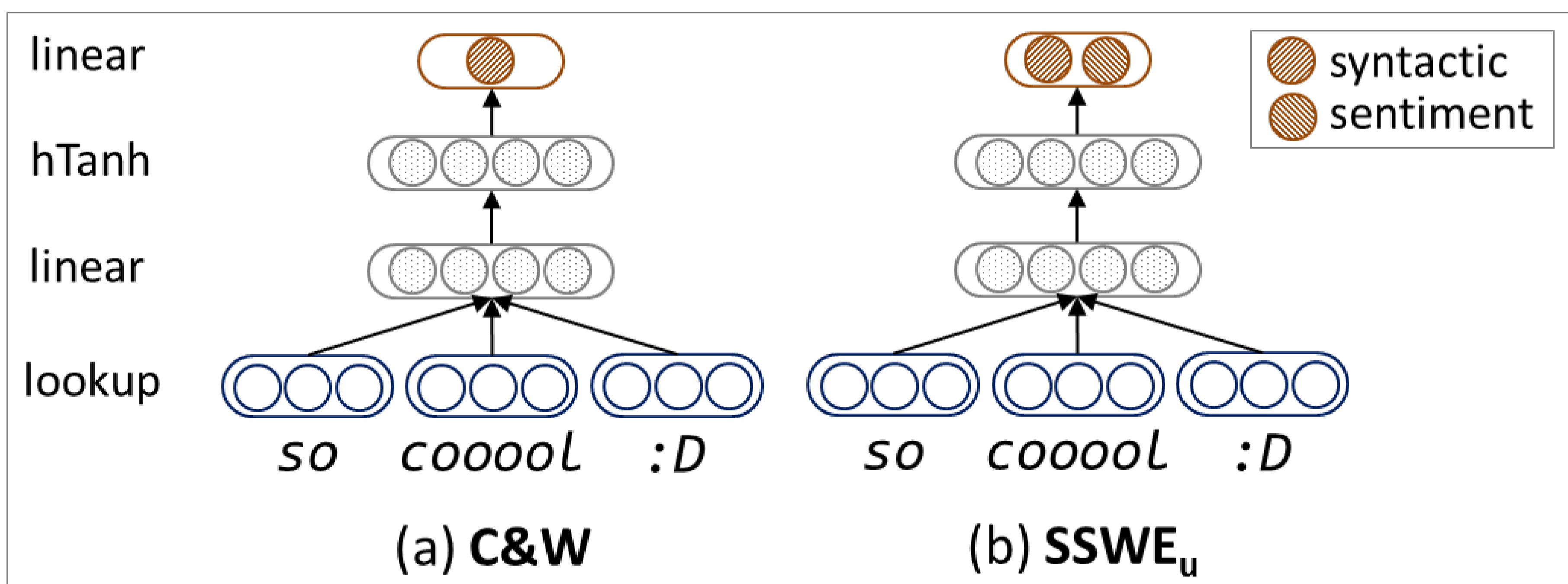
Test Dataset	Rank (From 50)
Tweet 2013	3
SMS 2013	2
Tweet 2014	2
Sarcasm 2014	24
Live Journal	5
Macro	12
Micro	2

2. Our Approach

- We learn sentiment-specific word embedding from massive tweets collected by positive/negative emoticons
- We apply SSWE as features for building the sentiment classification in a supervised learning framework.



4. Sentiment-Specific Word Embedding



• C&W

- Use the **contexts** of words
- Hinge loss

$$\max(0, 1 - f^{cw}(t) + f^{cw}(t^r))$$

• SSWE_u

- Use the **contexts** of words and the **sentiment** of sentences
- Hybrid hinge loss

$$\alpha \cdot \max(0, 1 - f^{cw}(t) + f^{cw}(t^r)) + (1 - \alpha) \cdot \max(0, 1 - \delta_s(t) \cdot f_1^u(t) + \delta_s(t) \cdot f_1^u(t^r))$$

5. Experiments

- Apply SSWE on positive/negative/neutral and positive/negative classification of tweets

Method	Positive/Negative/Neutral					Positive/Negative				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
SSWE	70.49	64.29	68.69	66.86	50.00	84.51	85.19	85.06	86.14	62.02
Cooooll	72.90	67.68	70.40	70.14	46.66	86.46	85.32	86.01	87.61	56.55
STATE	71.48	65.43	66.18	67.07	44.89	83.96	82.82	84.39	86.16	58.27
W2V	55.19	52.98	52.33	50.58	49.63	68.87	71.89	74.50	71.52	61.60
Top	74.84	70.28	72.12	70.96	58.16	--	--	--	--	--
Average	63.52	55.63	59.78	60.41	45.44	--	--	--	--	--

- Compare with other word embeddings on Twitter sentiment classification (results on SemEval2013)

